Natural Gradient based Blind Multi User Detection in QPSK DS-CDMA Systems

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***Abstract*-Blind Multi User Detection (BMUD) is the process of simultaneously estimating multiple symbol sequences associated with all users in the downlink of a Code Division Multiple Access (CDMA) communication system using only the received data. We propose to apply Natural Gradient based online Blind Source Recovery (NGBSR) techniques using either the feedforward or the feedback symbol recovery structures to achieve the global task of BMUD for QPSK DS-CDMA systems. The quasi-orthogonality of the spreading codes and the inherent independence among the various transmitted user symbol sequences form the basis of the proposed BMUD methods. The application of these algorithms is justified since a slowly fading multipath CDMA environment is conveniently represented as a linear combination of convolved independent symbol sequences. The proposed structures and algorithms demonstrate promising results as compared to the conventional detection techniques comprised of matched filters (MF), RAKE, subspace LMMSE and LMMSE receivers. Illustrative simulation results compare the BER performance of the two proposed online BMUD structures to the conventional detectors.**

I. INTRODUCTION

Code Division Multiple Access (CDMA) is an efficient spread spectrum technique in which multiple users share the same temporal and spectral resources [6]. In the downlink signal processing, each user is identified by a unique code, which is chosen to be "quasi-orthogonal" to the codes allotted to other users in the system. The Direct-Sequence Code-Division Multiple Access (DS-CDMA) is a promising data transmission technique capable of high data rates and immunity to channel noise. The signal energy is "spread" over a wide frequency range, which reduces the effect of fading channels. Other advantageous features include soft capacity limit, cell frequency reuse, soft handover of users etc. Wide bandwidth CDMA will be a dominant technology for the third generation (3G) wireless communication systems and forms an integral part of the UMTS/IMT-2000 and CDMA2000 standards [17].

In this paper, we apply our proposed linear BSR structures [8, 9, 14] to the case of QPSK signaling in DS-CDMA systems. As per our knowledge, this will be first such application of adaptive BSR techniques to QPSK DS-CDMA symbol recovery. QPSK is currently becoming the de-facto transmission format in CDMA/WCDMA systems. QPSK allows for more efficient utilization of the transmission medium as compared to BPSK. QPSK also provides improved synchronism between various parallel channels transmitted to the same user, e.g., the composite data and the control channels or multiple data streams etc.

Unlike the uplink communication channel, where all user codes are known and the base/controlling station possesses much higher signal processing capabilities, the downlink channel has a different set of constraints. The receiver (e.g., a mobile phone) just has the knowledge of a single self-identification code, and also has limited computational resources. The detector at the receiving end can be setup as either a single-user or a multi-user detector. While a single-user receiver basically estimates the desired signal for a desired user by modeling all the interfering users and disturbances as noise. A multi-user detector (MUD) [6] includes all the users in the signal model. This results in significant improvement [11]. However the optimal MUD [12] is computationally intensive and requires several system parameters to be known. In typical downlink signal processing, where many of the system parameters are unknown including the codes and the number of co-existing users at any instant of time, one can use the blind techniques for better estimate of the user signal [2, 8, 14, 15, 16].

In the conventional detection techniques for CDMA signals, only the second order statistics among the user codes are exploited but in most practical situations the user data symbols among themselves are independent. This is a powerful assumption, which enables one to apply the existing blind source recovery techniques to solve the detection problem in the multi user environment. Blind Source Recovery (BSR) in this context is the process of estimating the original user-specific symbol sequences independent of, and even in the absence of precise system identification [8, 9].

The received CDMA signal can be considered as a set of non-gaussian random variables generated by the linear convolutive transformation of statistically independent component variables [2, 3, 14]. This linear transformation accounts for the user codes, multiple channel paths and slowly fading channel symbol memory. Our goal is to estimate another linear transformation such that it counters, as best as possible, the effects of the first transformation resulting in the recovery of the original signals. A similar blind deconvolution approach for BPSK signals has been

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earlier described in [2, 3 and 14]. However, the adaptive algorithm in [2] does not represent the class of natural gradient algorithms [1, 8, 9] and fails to compare favorably to our proposed structures in [14]. Further, the proposed algorithms have competitive performance and do outperform traditional detectors such as matched filter (MF), RAKE [6, 11], linear minimum mean square (LMMSE) detectors [4, 15] and subspace LMMSE (sub LMMSE)[16] for the simulated SNR range from −10 to +20 dB.

II. DOWNLINK RECEIVER SIGNAL MODEL

We will consider a wide sense stationary slowly fading, multipath, downlink AWGN model. The received data in this case can be modeled as a multipath generalization of the model in [6] as

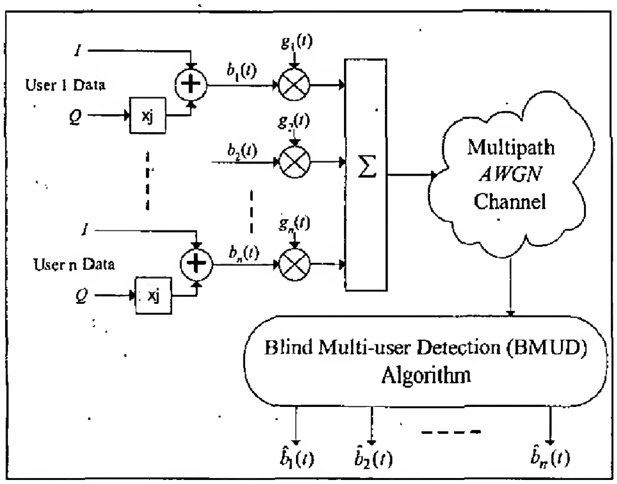

Fig. 1. Blind Multiuser Detection in a QPSK DS-CDMA system

$$r(t) = s(t) + n(t) \tag{1}$$

where

$n(t)$: represents the channel additive white gaussian noise

$s(t)$: represents the channel corrupted transmitted signal

$$s(t) = \sum_{n=1}^{N}\sum_{k=1}^{K} b_k(n)\sqrt{\varepsilon_{kn}(t)}\sum_{l=0}^{L-1} a_k(l)\, g_k(t-nT-\tau_l) \tag{2}$$

N : represents the total number of symbols during the observation interval

K : represents the total number of users during the observation interval

L : represents the total number of transmission paths per symbol

$b_k(n)$: represents the transmitted n^{th} QPSK symbol for the k^{th} user.

$\varepsilon_{kn}(t)$: represents the transmitted signal energy for the n^{th} symbol of the k^{th} user, also used for power control

$a_k(l)$: represents the fading factor or the path attenuation coefficients for l^{th} transmission path, and

τ_l : is the corresponding transmission delay for the l^{th} transmission path which typically satisfies the condition that $0 \le \tau_l \le T$ for all users.

$g_k(t)$: represents the signature code for the k^{th} user, generated by

$$g_k(t) = \sum_{m=0}^{M-1} \alpha_k(m)\, p(t - mT_c) \tag{3}$$

$\alpha_k(m); 0 \le m \le M-1$: is a PN code sequence for the k^{th} user containing M chips, $\alpha_k(m) \in \{\pm 1\}$

$p(t)$: is a chipping pulse of duration T_c

T : is the total code time, given by $T = MT_c$

The model presented by (1) and (2) can be written more compactly as a linear convolutive model comprising of the synchronously received chips for the current symbol as well as the distorted and delayed versions of chips for prior transmitted J-1 symbols also received during the same interval. The number of symbols J in the convolutive model is given by

$$J = \left\lceil \max(\tau_l) \big/ M \right\rceil + 1 \tag{4}$$

The convolutive model for the n^{th} received symbol can therefore be expressed as

$$\begin{aligned} r_n(t) = &\sum_{k=1}^{K} b_k(n)\sqrt{\varepsilon_{kn}}\sum_{l=0}^{L-1} a_k(l)\, g_k(t-nT-\tau_l) + n_n(t) + \\ &\sum_{j=1}^{J}\sum_{k=1}^{K} b_k(n-j)\sqrt{\varepsilon_{k(n-j)}}\sum_{l=0}^{L-1} a_k(l)\, g_k(t-(n-j)T-\tau_l) \end{aligned} \tag{5}$$

where, for a fading channel $\sqrt{\varepsilon_{k(n-j)}} \ge \sqrt{\varepsilon_{k(n-j-1)}};\ \forall j \ge 0$.

Under the condition that $\max(\tau_l) \le M$, $J = 2$ and the convolutive model reduces to an order 2 model, where the existing symbol is corrupted by only one previously transmitted symbol, i.e.,

$$r_n = \sum_{k=1}^{K}\left[b_{kn}\sqrt{\varepsilon_{kn}}\sum_{l=0}^{L-1} a_{kl}\bar{z}_{kl} + b_{k,n-1}\sqrt{\varepsilon_{k,n-1}}\sum_{l=0}^{L-1} a_{kl}\underline{z}_{kl} \right] + n_n \tag{6}$$

where

$\bar{z}_{kl} = [0 \ \cdots \ 0 \ \ g_k[M-\tau_l] \ \cdots \ g_k[1]]^T$,and

$\underline{z}_{kl} = [g_k[M] \ \cdots \ g_k[M-\tau_l+1] \ \ 0 \ \cdots \ 0]^T$

and τ_l is the discretized delay satisfying the constraint $0 \le \tau_l \le T$.

Alternately we can represent the model in a more compact matrix-vector form as

$$r_n = H_0 b_n + H_1 b_{n-1} + n_n \tag{7}$$

where

b_n and b_{n-1} are the K-d vectors of current and previous symbol for all the K users.

H_0 and H_1 are $M \times K$ mixing matrices given by

$$H_0 = \begin{bmatrix} H_{0,0} & H_{0,1} & \cdots & H_{0,K} \end{bmatrix}$$

$$H_1 = \begin{bmatrix} H_{1,0} & H_{1,1} & \cdots & H_{1,K} \end{bmatrix}$$

such that

$$H_{0,k} = \sqrt{\varepsilon_0} \sum_{l=0}^{L-1} a_{kl} \bar{z}_{kl} \tag{8}$$

$$H_{1,k} = \sqrt{\varepsilon_1} \sum_{l=0}^{L-1} a_{kl} z_{kl} \tag{9}$$

and $\varepsilon_0 \geq \varepsilon_1 > 0$ represent the energy of the current and the previous symbol respectively at the instant of observation.

III. NATURAL GRADIENT BLIND MULTI-USER DETECTION (BMUD) ALGORITHMS

As discussed in the previous section, the received signal comprises a noise-corrupted linear mixture of delayed and convolved user symbol sequences. It is reasonable to assume that the various transmitted symbol sequences are mutually independent as they are generated by independent sources. Assuming no preamble transmission to the receiver, both the transmitted sequence and the mixing matrices in the model (7) are unknown to the user. The only known entity to the user is the self-identification code. Other available prior information is the nature of transmitted data, which is QPSK corrupted by the multipath effects and channel distortion., i.e., it falls in the class of quaternary sub-gaussian distributions. We have enough information to apply the Blind Source Recovery (BSR) algorithms for BMUD in this case [8, 9, 13, 14].

Further we assume that the DS-CDMA channel is not over-saturated and $K \leq M$. The proposed BSR algorithms do not require any pre-whitening of received data. However, in DS-CDMA systems, M is chosen to be as large as possible and in general $K < M$. Therefore, it is computationally advantageous to pre-process the data for dimension reduction to K, which is the actual number of principal independent symbol components in the received data. The process of pre-whitening will also remove the second order dependence among the received data samples and some of the additive noise [2, 3, 7]. The data pre-whitening can be achieved either online using adaptive principal component analysis (PCA) algorithms or it may be done using an algebraic PCA estimate over a large batch (say N complex samples) of received data, i.e.,

$R = \begin{bmatrix} r_1 & r_2 & \cdots & r_{N-1} & r_N \end{bmatrix}$, with the correlation matrix

$$\Lambda_C = \frac{1}{N-1} R R^H \tag{10}$$

Then the whitening is achieved using the filtering matrix

$$W = D_s^{-1/2} V_s^H$$

where

D_s : represents the K-dim matrix of principle eigenvalues of the data correlation matrix Λ_C

V_s : represents the $K \times M$ matrix of corresponding principal eigen vectors of the data correlation matrix Λ_C, and

H: represents the Hermitian Transpose operator.

. The whitened version of (7) is given by

$$r_n^w = W\left(H_0 b_n + H_1 b_{n-1} + n_n\right) \cong \bar{H}_0 b_n + \bar{H}_1 b_{n-1} \tag{11}$$

where

r_n^w : represents the K-d received data at the n^{th} sampling instant

$\bar{H}_0, \bar{H}_1$: represent the equivalent square K-d mixing matrices for the current and the delayed symbols.

A. *Demixing Structures*

The natural gradient BMUD network for such a problem can be either in the feedforward or the feedback configuration [8]. We present the update laws for both cases; further the performance of the proposed algorithms is discussed and compared with conventional user detection algorithms [2, 14].

2) Feedforward BMUD Configuration: For the feedforward configuration, the BMUD stage output is computed as

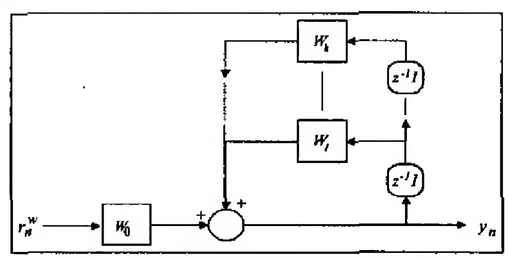

Fig. 3. Feedforward Demixing Structure

$$y_n = W_0 r_n^w + \sum_{k=1}^{K} W_k y_{n-k} \tag{12}$$

The update laws for this feedforward structure have been derived in [1, 8, 9] and are given by

$$\Delta W_0 \propto \left(I - \varphi(y_n) y_n^H\right) W_0 \tag{13}$$

$$\Delta W_k \propto \left(I - \varphi(y_n) y_n^H\right) W_k - \varphi(y_n) y_{n-k}^H \quad (14)$$

For initialization of the algorithm, W_0 is chosen to be either identity or dominantly diagonal, while the matrices W_k are initialized to have either small random elements or just as a matrix of zeros. Note that no matrix inversion is required for this algorithm.

1) Feedback BMUD Configuration: For the feedback configuration the output is estimated by

$$y_n = W_0^{-1}\left(r_n^w - \sum_{k=1}^{K} W_k y_{n-k} \right) \quad (15)$$

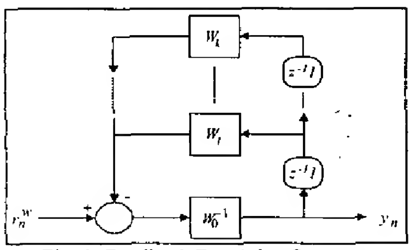

Fig. 2. Feedback Demixing Structure

The update laws for this structure using the natural gradient have been derived in [9]. The update law for the matrix W_0 is given by

$$\Delta W_0 \propto -W_0\left(I - \varphi(y_n) y_n^H\right) \quad (16)$$

While for the feedback matrices W_k, the update law is

$$\Delta W_k \propto W_0\left(\varphi(y_n) y_{n-k}^H \right) \quad (17)$$

where

$\varphi(.)$: represents an element-wise acting nonlinearity (score function) [1, 8, 9, 13]

I: represents a K-d identity matrix.

The matrices in this case are also initialized in a fashion similar to the feedforward case.

3) Conventional MUD Configurations: For the purpose of comparison, we apply the conventional user detection schemes such as the Matched Filter (MF), RAKE [6, 11], subspace Linear Minimum Mean Squared Error (sub LMMSE) [16] and the LMMSE estimators [4, 15]. The conventional estimators are computed using the following relations, respectively.

$$y_{kn,MF} = g_k^H r_n, \quad (18)$$

$$y_{kn,RAKE} = g_k^H \hat{H}^H r_n, \quad (19)$$

$$y_{kn,sub-LMMSE} = g_k^H V D^{-1} V^H r_n, \text{ and} \quad (20)$$

and

$$y_{kn,LMMSE} = g_k^H \hat{H}^H V D^{-1} V^H r_n \quad (21)$$

where

y_{kn}: represents the estimated output of the detector for the k^{th} user at the n^{th} instant

g_k: represents the self-identification code for the k^{th} user

D, V: represent the eigenvalues and the corresponding eigenvectors for the estimated data auto-correlation matrix Λ_C.

The output of all the detectors (including the proposed BMUD algorithms) is then fed to a nonlinear decision element to best estimate the recovered symbol $\hat{b}_{kn}$.

$$\hat{b}_{kn} = \psi(y_{kn}) \quad (22)$$

where $\psi(.)$: represents the (nonlinear) decision operator.

IV. SIMULATION RESULTS

The adaptation for the proposed natural gradient algorithms can be done either in batch or instantaneous modes. Although the asymptotic performance of the algorithms in batch mode is slightly better than the online mode [14], however the computational cost and the data storage requirements are prohibitive for practical BMUD implementations. In this paper, we primarily focus on using online update laws for the proposed algorithms.

The BMUD performance of the proposed algorithms is compared to the performance of the conventional symbol recovery algorithms using the Bit Error rate (BER) of the recovered symbol sequences [2, 14]. The convergence criterion is set to be a threshold on the L_2 norm of the difference between consecutive updates of recovery weight matrices. As the symbol sequences are directly estimated using the proposed technique, therefore, a data preamble is used for user identification.

An alternate performance comparison can be done for the synthetic simulation cases by computing diagonalization of the absolute value of the global transfer function. The global transfer function presents the combined effect of the complex mixing and demixing transfer functions. For the order 2 transfer functions simulated, the global transfer function for the natural gradient algorithms in the z-domain are given by:

$$G(z) = G_0 + G_1 z^{-1} \quad (23)$$

where, for the *feedback* algorithm

$$G_0 = W_0^{-1}\bar{H}_0 = W_0^{-1} W H_0 \quad (24)$$

$$G_1 = W_0^{-1}\left(\bar{H}_1 - W_1\right) = W_0^{-1}\left(W H_1 - W_1\right) \quad (25)$$

and for the *feedforward* algorithm

$$G_0 = W_0 \bar{H}_0 = W_0 W H_0 \quad (26)$$

$$G_1 = W_0 \bar{H}_1 + W_1 = W_0 W H_1 + W_1 \quad (27)$$

A. Simulation Setup

For simulation, a user's composite BPSK data stream is split into quadrature components by a serial-to-parallel converter (S/P). These QPSK data stream for each user is then spread by a user's allotted signature code. The transmitted chips are generated by a summation of all the corresponding user's chips. The user's signature codes are chosen to be gold codes of length 31 (i.e., M=31) [5]. The transmitted chips arrive at the receiver after propagation through an AWGN multipath channel. The receiver is assumed to be in synchronism to the transmitter. Due to space limitations, only simulated results for 4 users (13% capacity) and 25 users (80% capacity) in the system are presented.

For the proposed BMUD algorithms, the score function is chosen as follows, see [13]

$$\varphi_i(y_i) = y_i - \left(\tanh\left(\mathrm{Re}\{y_i\}\right) + \tanh\left(\mathrm{Im}\{y_i\}\right)\right) \qquad (28)$$

where, y_i : represents the estimated output at the i^{th} iteration

The learning rate is initialized at 0.1 and then exponentially decayed. As the transmitted signals are QPSK, the final symbol decision is done using a sign function separately on both the real and imaginary parts of the recovered symbol.

$$\psi(y_n) = sign\left(\mathrm{Re}\{y_n\}\right) + sign\left(\mathrm{Im}\{y_n\}\right)i \qquad (29)$$

For the sake of simulation, we assume that there are three multipaths (L=3), with delays of 0, 1 and 2 chips. The multipath channel co-efficients are assumed to be complex, i.e., they apply both scaling and rotation to the propagated signal constellation. Since $L \leq M$, the demixing network is chosen to be order 2. The channel co-efficients are assumed known for the RAKE and LMMSE detectors. Further, we also assume that the sign ambiguity for all the detection schemes can be resolved using the frame synchronous pilot bits in the composite user data streams. We now consider two cases for the multipath channel co-efficients.

1) Simulation I: Primary Path Phase Known: In this case, it is assumed that the phase of the primary path is known. Therefore the multipath attenuation co-efficient are chosen to be $a_k = [1 \quad 0.6+0.2i \quad 0.5+0.3i]^T$ and $a_k = a_k/\|a_k\|$. A performance comparison of all the algorithms for this simulation is shown in Fig. 4(b). It is evident that the proposed BMUD algorithm is the best of all for both lower and higher congestion of the network. For the lower congestion case, sub LMMSE and LMMSE are quite close, but at higher congestion sub LMMSE is worse as compared to even MF.

2) Simulation II: Primary Path Phase Unknown: Now it is assumed that the phase of the primary path is not known. The multipath attenuation co-efficient are chosen to be $a_k = [0.8+0.6i \quad 0.6+0.2i \quad 0.5+0.3i]^T$ and then normalized as before. A performance comparison of all the algorithms for this simulation is shown in Fig. 4(c). In this case, it is observed that the performance of MF and sub LMMSE is severely degraded. The BER of the proposed BMUD detectors (although more than simulation I) is still better than the LMMSE detector, which uses the perfect knowledge of the channel.

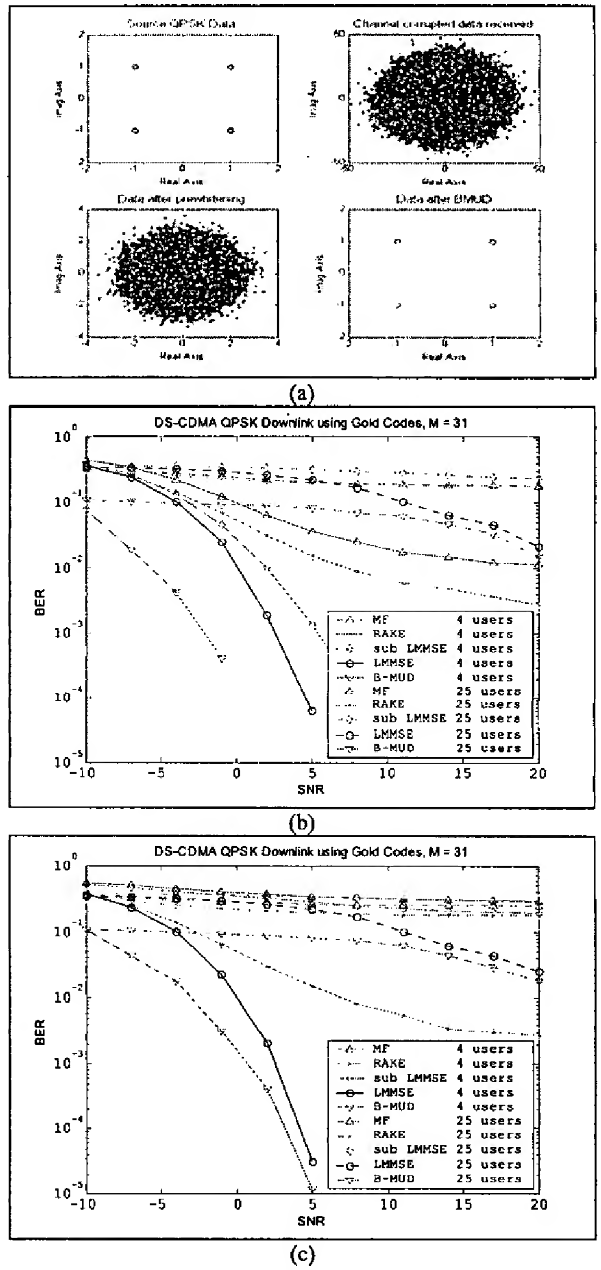

Fig. 4. BER results for QPSK DS-CDMA: (a) signal constellation after channel propagation and recovery by BMUD, Performance Comparison of Algorithms with (b) phase of reference path known, (c) phase of reference path unknown.

Notice that at poor SNR scenarios, LMMSE performance is very close to RAKE detector, but the proposed BMUD algorithms based on BSR feedforward and feedback structures exhibit one-third BER as compared both LMMSE and RAKE. Further, the BMUD algorithms maintain their performance edge even under conditions of high network congestion and lower SNR, which indicates their robustness and usefulness for DS-CDMA systems.

Fig. 5 graphically presents a typical absolute global transfer function achieved using BMUD, i.e., the convolution of the mixing environment and the demixing network transfer functions. Presented below is the $G(z)$ computed for 8 users in the network. We observe that the BMUD algorithm has identified all the users successfully. The global transfer function exhibits permutations, scaling and sign ambiguities, which are inherent in BSR solutions. In DS-CDMA, this is overcome using a data preamble/pilot for user identification.

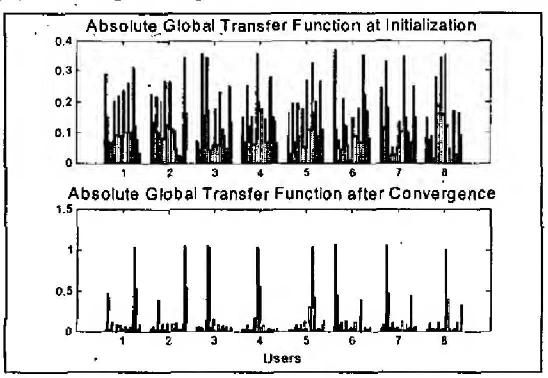

Fig. 5. Typical Absolute Global Transfer Function for K=8

V. CONCLUSIONS

We have introduced effective blind source recovery (BSR) algorithms in the feedforward and feedback configurations to the realm of QPSK DS-CDMA blind multi-user detection (BMUD) and recovery. The proposed algorithms outperform the conventional DS-CDMA detection techniques with significantly reduced BER even under conditions of congestion and low SNR. The instantaneous versions of the algorithms are preferred for BMUD applications as they have lesser computational complexity and smaller memory requirements. The BMUD is a promising technique as there is no need of precise synchronization required similar to the conventional techniques. The problem formulated in this paper is directly applicable to the various QPSK CDMA applications that include newer GPS enhancements, Wireless LAN: ad-hoc and ATM networks to name a few.

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